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Evaluation of proactive maintenance policies on a stochastically dependent hidden multi-component system using DBNs

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ABSTRACT

In complex systems with stochastically dependent components which are not observed directly, determining an effective maintenance policy is a difficult task. In this paper, a dynamic Bayesian network based maintenance decision framework is proposed to evaluate proactive maintenance policies for such systems. Two preventive and one predictive maintenance strategies from a cost perspective are designed for multi-component dependable systems which aim to reduce maintenance cost while increasing system reliability at the same time. Tabu procedure is employed to avoid repetitive similar actions. The performances of the policies are compared with a reactive maintenance strategy and also with each other using different strategy parameters on a real life system confronted in thermal power plants for six different scenarios. The scenarios are designed considering different structures of system dependability and reactive cost. The results show that the threshold based maintenance which is the predictive strategy gives the minimum cost and maintenance number in almost all scenarios.

1. Introduction

The complexity of systems has recently increased due to different types of dependencies and partial observability of their components. To survive in today's competitive environment, keeping systems available is essential. Otherwise, deliveries to the customer are delayed, which could result in penalty cost, loss of trust and even loss of customer. The most effective way to avoid these is to maintain systems regularly. In the most common sense, maintenance is the set of tasks carried out to sustain the operation of the established order in a factory. Maintenance can be mainly divided into two as proactive and reactive [1]. Reactive maintenance is carried out to correct a malfunction or to remove an emergency situation whereas proactive maintenance is performed to avoid possible downtimes before the system stops because of a failure. It is a known fact that proactive maintenance is able to reduce cost considerably if applied effectively. However, it does not completely prevent the occurrence of unexpected failures [2]. So, it is also necessary to carry out reactive maintenance immediately to ensure that the fault is remedied as soon as possible.

Proactive maintenance can be grouped under two headings as preventive and predictive [3]. In the former, the system is maintained at predetermined intervals, while in the second, a certain criterion which generally relates to the reliability of the system must be met to maintain the system. Preventive maintenance can be further classified as age-based and block-based [4]. The age-based strategy sets the proactive maintenance times with respect to the age of the equipment whereas in the block-based, fixed time intervals are used to schedule the proactive maintenance. Shafiee and Finkelstein [5] propose a group maintenance strategy based on the age of the components for a multi-unit system. A block-based maintenance strategy for a single component which is used randomly is developed by De Jonge and Jakobsons [6]. Nguyen et al. [7] introduce a two-level predictive maintenance policy for a system consisting of AND and OR gates in which proactive maintenance times are determined according to the system reliability whereas the components to be maintained are selected considering the economic dependency in the system. Our study is similar to the last one in the sense that it tackles multi-component system maintenance, but there exist also probabilistic gates, stochastic dependency and partial observability in our system.

Traditionally, dependencies have been identified in three ways: structural, economic and stochastic [8]. Another type, resource dependency, has also been recently described by [9]. In the first one, two components that are dependent on each other must be maintained together. That is, even if only one of them fail, the other must also be disassembled [10]. Economic dependency means that if a group of components are maintained together, total maintenance cost is either reduced or increased compared to the total of individual maintenance costs of the respective components [11,12]. Sometimes, the two mentioned dependencies are considered together [13]. In the third one, the

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deterioration of one component may increase the likelihood of failure of the other dependent component or shorten its life [14]. The last type of dependency exists if limited resources are available for the maintenance activities. Various methods have been used in the literature to model the dependencies among components. The most well-known are event tree analysis [15], failure tree analysis [16] and bow tie analysis [17]. These methods use only two-state decision mechanism and they rely only on the static structure not considering the dynamic behavior of the system.

Markov models and their decision network based variants are used in maintenance area, especially when the system is hidden. A methodology, based on hidden Markov model and belief rule, to estimate the failures of a hidden system is proposed by Zhou et al. [18] for multi-state systems. On the other hand, such systems use sensors providing information about when to perform maintenance [19]. A method combining discrete time Markov chain with $\bar{X}$ control chart is proposed by Xiang [20] for the preventive maintenance of a single machine system. Papakonstantinou and Shinozuka [21] suggest to implement partially observable Markon decision process (POMDP) for the maintenance planning of infrastructure systems with large state spaces. Byon et al. [22] use POMDP to find the optimal maintenance strategy of wind turbines. In all of these studies, a system of one component is considered. Simulation which enables to model more complex systems is also used in the area of maintenance optimization. An approach with discrete event simulation is proposed by Alrabghi and Tiwari [23] to determine the most appropriate maintenance strategy for each variable in a complex system. A strategy for condition based maintenance using Monte Carlo simulation and Bayesian control chart is introduced by Wang [24]. These studies handle small-size systems or a part of a complex system where none of the dependency types are considered.

Recently, Bayesian networks (BNs) have come insight as another method used in this context. Unlike the other methods mentioned above, structural and stochastic dependencies among components, and partial observability can be easily modeled using BNs. Dynamic Bayesian networks (DBNs) add time dimension to BNs which enables them to model dynamic systems through a given horizon under collected evidence. Hence, they are preferable for predicting the system reliability [25] and risk assessment [26]. There are also limited number of studies where DBNs are used for maintenance planning. Nielsen and Sørensen [27] present and compare two different approaches based on DBNs for planning inspections and maintenance. Hu et al. [28] propose a method for planning an opportunistic predictive maintenance using DBNs and HAZOP methodology. Cai et al. [29] use DBNs to compare perfect and imperfect repair, and preventive maintenance for a subsea blowout preventer. Muller et al. [30] propose an e-maintenance approach, based on probabilistic modeling, which can dynamically monitor system degradation to adjust the time of proactive maintenance. These studies either have very few components or they do not consider cost in maintenance decisions.

In this study, a DBN based maintenance decision framework is proposed to evaluate proactive maintenance policies from a cost perspective for stochastically dependent hidden multi-component systems. It is shown that DBNs provide an efficient environment for modeling dependencies and deterioration in the maintenance problem of such systems. A generic proactive maintenance algorithm with a tabu procedure is developed within the framework. Two preventive and one predictive cost-effective maintenance strategies are evaluated with different policy parameters. A tabu procedure is proposed in order to prevent selecting the same component for maintenance consecutively. A case study is presented to analyze the results of the DBN based proactive maintenance strategies on a system within thermal power plants. The proactive strategies are compared with each other and also with the reactive strategy under several scenarios to diagnose the structure and parameters where proactive maintenance yields satisfactory results.

The study is organized as follows: Section 2 gives the basics of the methodology used. The proposed DBN based maintenance decision framework is presented in Section 3. A case study for the application of the proposed framework on a thermal power plant system is given in Section 4. Computational results are analyzed in Section 5. Lastly, conclusion and future studies are argued in Section 6. Nomenclature used in the paper is tabulated in Table 1.

2. Methodology

We use dynamic Bayesian networks as the basis of the maintenance decision framework we propose. DBNs enable modeling complex interactions, dependencies and deterioration in the system using conditional probabilities, and facilitate inference calculations by exploiting conditional independence between variables.

2.1. Dynamic Bayesian networks

Bayesian networks are probabilistic graphical models that represent conditional dependencies among variables via directed acyclic graphs. DBNs are constituted by adding time dimension to BNs to evaluate also the effect of time on the model variables and the dependencies. A DBN consists of several BNs each of which represents a specific time slice of the DBN. The joint probabilities of the variables in a DBN can be calculated as in Eq. (1) where T is the number of time slices, N is the number of random variables in a time slice, X_t^i is the ith node in time slice t, $Pa(X_t^i)$ represents the parents of X_t^i, X_t denotes all variables in time slice t, and finally $X_{1:T}$ represents all variables in the network, i.e, $X_1, X_2, \ldots, X_T$.

$$P(X_{1:T}) = \prod_{t=1}^{T}\prod_{i=1}^{N} P(X_t^i | Pa(X_t^i)). \tag{1}$$

2.2. A representative DBN model

A representative DBN model which consists of three components, two processes and one observation node is depicted in Fig. 1a to show the types of systems that we are tackling in this study. The model is unrolled for only two time slices for a compact representation. The nodes and solid arrows represent the random variables and the dependencies between these variables respectively in a time slice whereas the dashed arrows between two time slices model the dynamic behavior of the system.

In Fig. 1, C_A, C_B and C_C are the maintainable components affecting the operation of the system. Nodes P and S represent the processes showing the interaction of the components affecting it while S is the final process node. The variable O represents the observation node that allows the system to be observed from outside. There are stochastic dependencies in the model. Component B is stochastically dependent on A (with one period lag) whereas C is stochastically dependent on B. In the system, components and processes are hidden. However, they can be inferred partially from the observation node. Components start at their best states at the beginning of the planning horizon and deteriorate with constant transition probabilities.

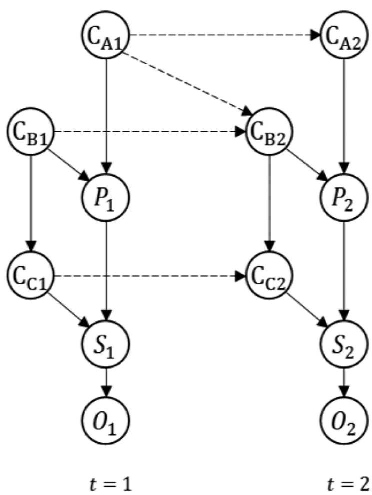
In DBNs, it is not possible to model the maintenance of the components directly. To give the effect of maintenance, an action node is defined for each component. Fig. 1b shows the same DBN model with the action nodes. By this way, once it is decided to maintain a component or not, the state of the related action node is changed according to the decided maintenance activity.

3. DBN based maintenance decision framework

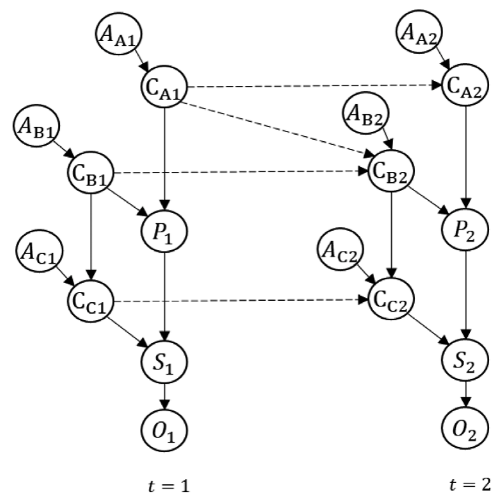
Özgür-Ünlüakın et al. [31] propose eight number-based maintenance methods with two different efficiency measures to select a component at a reactive maintenance time. These methods are enriched by considering also the maintenance cost of components to minimize the total horizon cost and experimented on reactive maintenance strategy.

Table 1
Nomenclature.

I	Set of components	ε	Accumulated evidence consisting of the replacement history
I'	Set of eligible components for maintenance	$CIPM$	Constant Interval Proactive Maintenance
i	Index for components	$DIPM$	Dynamic Interval Proactive Maintenance
i^*	The component selected for maintenance	$ThPM$	Threshold based Proactive Maintenance
t	Index for time periods	pci	Proactive constant interval for CIPM
T	Planning time horizon	$CIMT$	Array of constant interval maintenance periods
$TotCost$	Cumulative total maintenance cost	pdi	Proactive dynamic interval for DIPM
$Cost_i$	Total maintenance cost of node i	pmt	Next proactive maintenance time for DIPM
AC_i	Maintenance action cost of node i	thr	Threshold level of ThPM
AD_i	Action duration of node i	$TabuDur$	Tabu duration
DC_i	Unit downtime cost of node i	$TabuDurList$	Array that keeps the tabu duration of each component
W	Best state of the components and the system	$TabuList$	Array that keeps the tabu components
F	Worst state of the components	RAH	Regenerative air heater
R	Worst state of the observation node	RM	Reactive maintenance
ef_{it}	Efficiency measure of component i in period t	PM	Proactive maintenance
C_{it}	State of component i in period t, $i \in I$	SD	Standard deviation
S_t	State of the system in period t	GH	Games Howell test results
O_t	State of the observation node in period t	Tk	Tukey test results



(a) A DBN model.



(b) A DBN model with action nodes.

Fig. 1. A representative DBN model.

It is found that Fault Effect Look Ahead method with worst state probability measure (FEL_{fp}) is the most satisfactory among the eight [32]. Hence, it is decided in this study to employ FEL_{fp} with cost effect to evaluate the alternative maintenance actions.

In FEL_{fp} method, when a reactive or proactive maintenance decision is taken, the worst state probabilities of all components in the "next" period are investigated and the component which has the maximum is selected to be maintained. To consider also the maintenance cost of components, this measure is divided by the cost of the respective component. However, in order to be fair to both cost and probability, the cost values in the measure are normalized according to the failure probabilities of the components at the next time. The efficiency measure, ef_{it}, enriched with the cost effect is given in Eq. (2) where $C_{i,t+1}$ denotes the state of the component i in period $t+1$, "F" and "R" represent the worst state of component i and observation node, O_t, respectively while $Cost_{it}^N$ is the normalized cost of performing maintenance on component i at time t. Here, ε denotes the accumulated evidence consisting of the replacement history.

$$ef_{it} = P\left(C_{i,t+1} = \text{“}F\text{”} \mid \varepsilon \cup \{O_t = \text{“}R\text{”}\}\right) / Cost_{it}^N \quad (2)$$

We design a DBN based maintenance decision framework for the proactive maintenance (PM) strategies of hidden multi-component dependable systems. We propose a two-level hierarchical solution approach where the maintenance time is determined in the first level with respect to the strategy used and then the component to be maintained is decided in the next level according to the cost effective FEL_{fp} method and the tabu procedure. Two preventive strategies which are constant interval proactive maintenance (CIPM) and dynamic interval proactive maintenance (DIPM), and one predictive strategy that is threshold based proactive maintenance (ThPM) are evaluated using DBNs. In addition to this, a reactive maintenance (RM) methodology is employed to be compared with the proactive maintenance strategies.

3.1. Reactive maintenance strategy

Reactive maintenance consists of all kinds of activities to make the necessary functions of the system available again after a malfunction or an emergency situation occurs in the system. The emergency situation in the study is assumed to be the case that the observation node "O" of the system is in its worst state. In the strategy, the observation is sampled at each time point and if it is in "R" state, a component is decided to be maintained using the cost effective FEL_{fp} method from the eligible component list, I' which keeps the set of components that have not been maintained at that time point. Such a list is needed because at a time point, the observation may not be fixed with one maintenance action. So, components should be continued to be maintained until the exigency goes away. The pseudo code of the RM strategy is given in Algorithm 1.

Algorithm 1 DBN Based Reactive Maintenance Algorithm

Set t=1
while $t \leq T$ **do**
  Set eligible components $I' = I$
  Sample O_t
  while (O_t =“R”) and (I' is not empty) **do**
    Evaluate $ef_{it}, \forall_{it}$
    Determine $i^* = argmax\{ef_{it} : i \in I'\}$
    Update $\varepsilon \leftarrow \varepsilon \cup \{A_{i^*t} \leftarrow 1\}$
    Calculate $Cost_{i^*} = AC_{i^*} + AD_{i^*} \times DC_{i^*}$
    Calculate $TotCost = TotCost + Cost_{i^*}$
    Sample O_t
    Update $I' \leftarrow I' | \{i^*\}$
  end while
  $t \leftarrow t + 1$
end while

3.2. Decision making in proactive maintenance

Fig. 2 depicts the iterative decision making flow for a generic proactive maintenance strategy. Observable node is simulated at each time period according to its inferred probability distribution. If an undesirable signal, “R”, is observed which almost indicates an unexpected failure of the system, maintenance action(s) should be performed under reactive maintenance philosophy. Maintenance decision is also taken at a time point if one of the following proactive maintenance conditions occurs at that time: (1) If a planned CIPM time comes, (2) If a dynamically updated DIPM time comes or (3) If the reliability of the system falls below a specified threshold. It should be noted that, although a proactive maintenance time comes but if the observation is undesirable, reactive maintenance is applied. This is because of the assumption that the observation is taken every morning, but proactive maintenance is planned in the evening so as not to hinder the proposed production. Moreover, if a proactive maintenance is initiated, it is assumed that only one activity can be done proactively because of the limited resource allocated. Further activities, if needed because of an undesirable succeeding observation, are performed in reactive maintenance conditions.

3.3. Tabu procedure

If proactive maintenance is performed frequently, it is possible to face with a situation of selecting the same component consecutively. Because in such cases, since the failure probability of all components are at a low level and almost not so different from each other, their cost values stand out in determining the component to maintain. To prevent this situation, a tabu list inspired from the well known tabu search algorithm in meta-heuristics [33] is kept. After a component is maintained proactively or reactively, it is added to this list and it cannot be maintained proactively until its tabu duration expires. Tabu list is considered only at time points where proactive maintenance is initiated whereas being at a reactive maintenance time is an aspiration criterion which enables also the selection of the components that are in the tabu list. Hence, if further maintenance is needed at a proactive maintenance time because of an undesirable observation received, selection is done among the components that are not tabu.

3.4. Proactive maintenance strategies

Based on DBNs, two preventive maintenance policies, CIPM and DIPM [34] inspired by block-based and age-based strategies and a threshold based proactive strategy (ThPM) inspired by [35] are designed and evaluated for multi-component dependable systems.

3.4.1. Constant Interval Proactive Maintenance (CIPM)

The purpose of this strategy is to schedule preventive maintenance at fixed time points, similar to block-based maintenance, in the planning horizon. Whenever the system is in a state of emergency before reaching the CIPM time, reactive maintenance is urgently performed. In this case, the predetermined maintenance schedule is not updated according to this reactive maintenance. Here, preventive maintenance is carried out on only one component on the contrary to the block-based maintenance where the whole system is repaired.

3.4.2. Dynamic Interval Proactive Maintenance (DIPM)

In this strategy, preventive maintenance is scheduled with a specific time interval in the planning horizon as in CIPM but here, whenever a reactive maintenance is carried out, the next preventive time is shifted as in age-based maintenance. Hence, preventive maintenance times are determined dynamically. However, it is applied on only one component whereas in the age-based maintenance, the whole system is repaired.

3.4.3. Threshold Based Proactive Maintenance (ThPM)

Both CIPM and DIPM are preventive maintenance strategies and schedule proactive maintenance at certain time points either by using a constant or a dynamic interval without considering the condition of the system. In order to determine the maintenance times adaptively, a predictive maintenance strategy which considers the system reliability is also set up to decide on a proactive maintenance. The reliability of the system represented by the main process node in the model, is estimated in the beginning of every period and if it is less than a given threshold, a proactive maintenance is scheduled at the end of that period. This strategy aims to reduce unnecessary proactive maintenance by taking into account the system condition.

3.4.4. Generic algorithm for the proactive maintenance strategies

The implementation of CIPM, DIPM and ThPM within the proactive maintenance framework is given in Algorithm 2 where the strategy to be implemented and its parameter are given as inputs. This generic pseudo code differs in initiating and updating parameters, depending on the strategy used. In the algorithm, Line 19 identifies the maintenance time. If the observation node results in “R”, it always indicates a reactive maintenance. Otherwise, a proactive maintenance can be decided depending on the values of the three boolean operators of the proactive maintenance strategies. If CIPM is used, constant proactive maintenance times are kept in the CIMT array constituted according to the proactive constant interval (pci). When such a time comes and proactive maintenance is performed, the first item of the array is deleted. If DIPM is used, the dynamic proactive maintenance interval (pdi) is given as the input to the algorithm. Proactive maintenance time (pmt) is updated by adding this interval to the current period if a maintenance is performed.

When ThPM is applied, a threshold level (thr) is determined as the input parameter. $P(S_t = \text{“}W\text{”}|\varepsilon)$ in Line 19 of Algorithm 2 represents the system reliability under the accumulated evidence, ε. This reliability is obtained by the dynamic junction tree inference algorithm in BNT toolbox [36]. The threshold level is updated to zero after a proactive maintenance is decided to satisfy the condition that proactive maintenance is to be performed at most once at a period because of the limited resource allocated. By this, the boolean operator comparing the reliability of the system with the threshold level never returns a true value after a proactive maintenance at a period and hence, possible multiple proactive maintenance is avoided.

After sampling the observation node, if reactive maintenance is required, the set of eligible replaceable components, I', contains all components. Otherwise, I' consists of components that are not in the tabu list. Although proactive maintenance condition is met, if the observation node is in “R” state, reactive maintenance is applied. Otherwise, one of the proactive maintenance strategies is applied. Proactive and reactive maintenance costs differ due to action cost (AC_i),

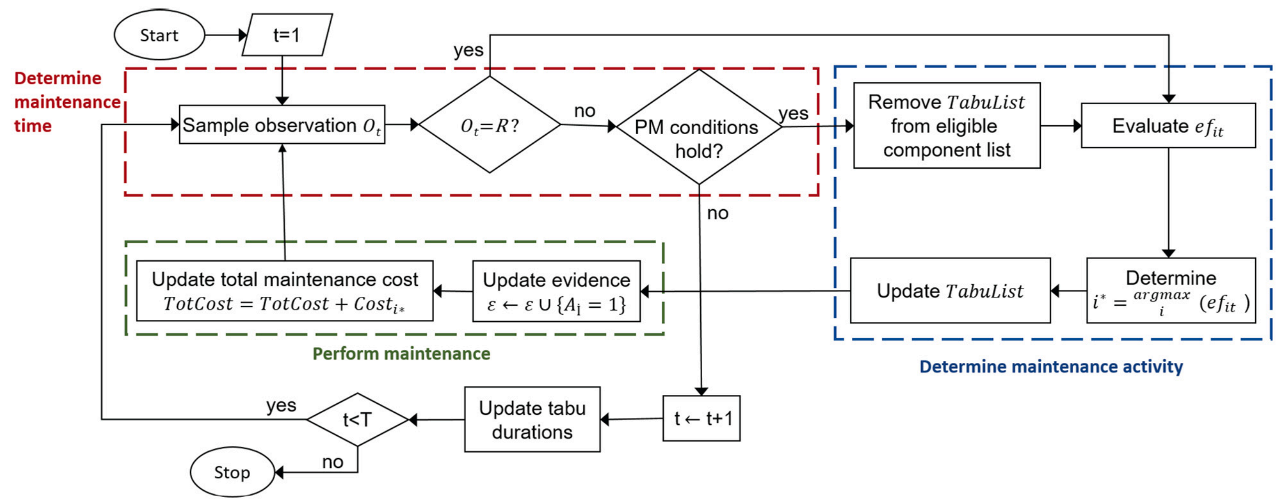


Fig. 2. Decision making flow of PM strategies.

Algorithm 2 DBN Based Proactive Maintenance Algorithm

Input Strategy, $pci, pdi, Threshold, TabuDur$
if Strategy = "CIPM" **then**
  Input $CIMT = [pci * 1, pci * 2, ..., pci * \lfloor T/pci \rfloor]$
end if
if Strategy = "DIPM" **then**
  Set $pmt = pdi$
end if
Set $t = 1$
while $t \leq T$ **do**
  if Strategy = "ThPM" **then**
    Set $thr = Threshold$
  end if
  Sample O_t
  if $O_t \neq$ "R" **then**
    $I' \leftarrow I | TabuList$
  else
    $I' \leftarrow I$
  end if
  while $((O_t = \text{“}R\text{”})$ or $(t = CIMT(1))$ or $(t = pmt)$ or $(P(S_t = \text{“}W\text{”}|\varepsilon) < thr))$ and (I' is not empty) **do**
    if (Strategy = "CIPM") and $(CIMT(1) = t)$ **then**
      Update $CIMT(1) = [\,]$
    else if Strategy = "DIPM" **then**
      Update $pmt = t + pdi$
    else if Strategy = "ThPM" **then**
      Update $thr = 0$
    end if
    Evaluate $ef_{it}\ \forall i \in I'$
    Determine $i^* = argmax\{ef_{it} : i \in I'\}$
    $TabuDurList(i^*) = TabuDur$
    Update $\varepsilon \leftarrow \varepsilon \cup \{A_{i^*t} \leftarrow 1\}$
    Calculate $Cost_{i^*} = AC_{i^*} + AD_{i^*} \times DC_{i^*}$ (in reactive or proactive conditions according to O_t)
    Calculate $TotCost = TotCost + Cost_{i^*}$
    Update $I' \leftarrow I' | \{i^*\}$,
    Sample O_t
  end while
  $t \leftarrow t + 1$
  Update $TabuDurList$
  $TabuList \leftarrow \{j : TabuDurList(j) > 0\}$
end while

action duration (AD_i) and downtime cost (DC_i) values of components. Hence, the iteration cost ($Cost_i*$) is calculated according to the observation. Total cost is updated by adding the iteration cost. After each maintenance, the component that is maintained is removed from the eligible component list, so if a maintenance is required again on that period, another component is selected from the updated list. When a component is maintained, it is added to $TabuList$ in order to prevent selecting the same component in subsequent proactive maintenance periods for a limited time, $TabuDur$. Tabu duration of components are kept in $TabuDurList$ which is updated at each period.

4. Application of the proposed framework to the RAH system

Proactive maintenance strategies given in Section 3.4 are implemented within the proposed DBN based maintenance decision framework on a regenerative air heater (RAH) which is a multi-component system used in air–gas system of thermal power plants.

4.1. DBN modeling

Multi-component systems are generally very complex because of the relationships and dependencies among them. DBNs provide a very efficient environment to model such relationships and dependencies by conditional probabilities. Özgür-Ünlüakın et al. [31] develop a DBN model for the RAH system where the relationships and dependencies among the components are determined based on expert opinions in the power plant and the conditional probabilities[1] in the model are defined according to transition rates, historical data and expert judgment. In this paper, we use the same DBN model depicted in Fig. 3 to implement the proactive maintenance strategies under the proposed framework. In [31], the DBN model is used to develop a number-based reactive maintenance methodology without considering the maintenance costs of the components where the aim is to minimize the number of components that undergo reactive maintenance. Different from [31], this study focuses on the evaluation of proactive maintenance strategies with the aim of minimizing the total proactive and reactive maintenance cost.

The RAH system includes two parallel motor groups. In each motor group, there are four components (ball bearing, winding-insulation, rotor-shaft and hub reduction gear) and two process nodes (rotor rotation, HRG rotation). Apart from the motor groups, RAH also consists of two other components (RAH insulation and honeycombs), two process nodes (regenerative air heater rotation and RAH exit temperature) and an observation node (RAH measured temperature) which indicates system failures. To give the effect of the maintenance actions, an action node is modeled for each component.

[1] Available in https://drive.google.com/open?id=1eR5d2ab1kXyeFgn55H9mly-BMhXg747g.

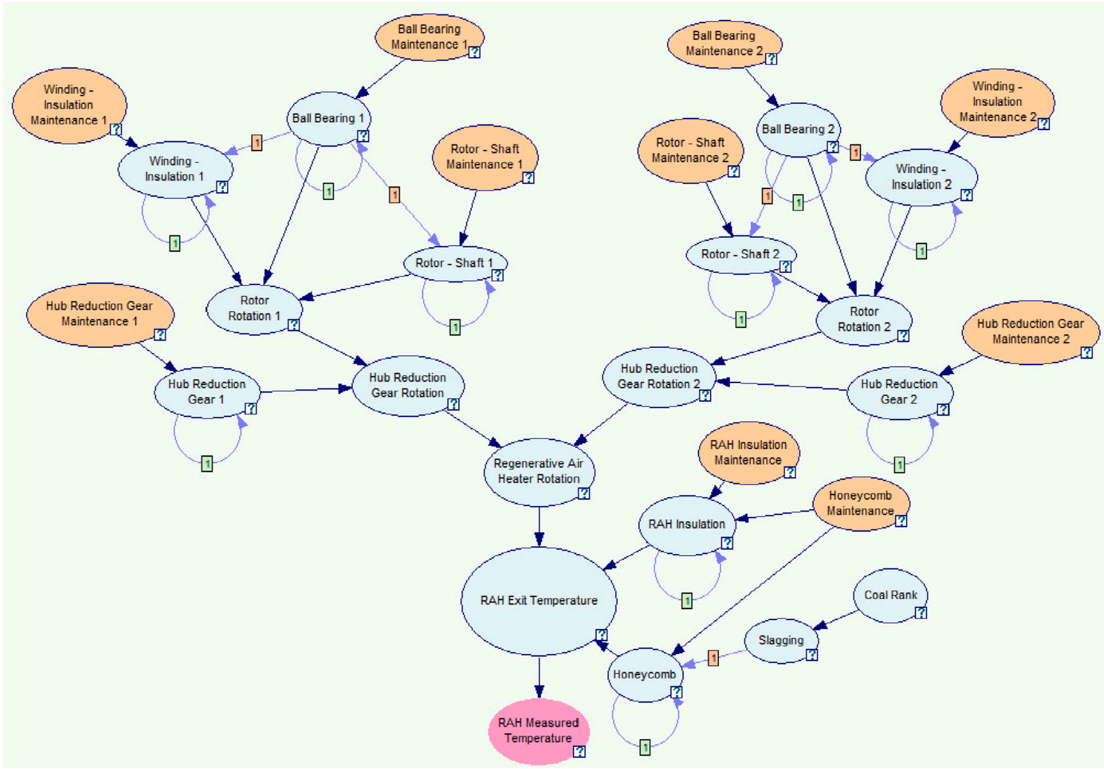


Fig. 3. The DBN model of the RAH system [31].

4.2. Maintenance costs

Maintenance cost of a component is calculated as in Eq. (3). It consists of action cost and downtime cost. Action cost includes only maintenance-related costs. Action duration covers the duration from the start of the maintenance until the time it ends. During a reactive maintenance, production is not possible. Because of this, until maintenance is completed and the plant restarts production, a downtime cost incurs. However, the RAH system consists of two parallel motor groups, and it is not required to stop for the proactive maintenance of a component in these motor groups. Hence, in proactive maintenance, no downtime cost incurs for the components other than the honeycomb and the RAH insulation.

$$Cost_i = AC_i + AD_i \times DC_i \tag{3}$$

Proactive and reactive maintenance costs and durations are determined according to the information given by the thermal power plant considered and are presented in Table 2. 181 kw of electricity is generated per hour in the plant. 35% of the production is supplied to the domestic market where electricity prices and demands are determined on a daily basis whereas 65% is supplied to firms on bilateral contracts where electricity price is determined by agreements. While calculating the downtime cost per each hour of the proactive maintenance, the overhead expenses of the power plant and the lost income based on the current price for the domestic market and the contract price for bilateral agreements are considered.

If the committed electricity cannot be supplied to the customer (domestic market or the firms) because of an unexpected downtime due to a reactive maintenance, a penalty payment must be made based on the current electricity price. Hence, this penalty cost is included in the reactive downtime cost. When the current electricity price is taken as 0.40 TL/kw and the price agreed with the firm is taken as 0.30 TL/kw, the unit downtime costs for proactive and reactive maintenance are calculated approximately as 40,000 TL/h and 50,000 TL/h respectively. It is important to note that these costs incur because the plant does not produce electricity due to a maintenance or a failure in the RAH system. However, since the thermal power plant has two parallel air–gas lines, when a line fails, the parallel one continues to work with 50% capacity. So, the unit proactive and reactive downtime costs are taken as 20,000 TL/h and 25,000 TL/h respectively.

4.3. Implementation insights

Modeling and simulation studies in this study are done using Matlab BNT-toolbox [36]. In real life, a DBN modeler such as Genie [37], which is also used in this study to provide the preview of the model given in Fig. 3, can be used for implementation. In the beginning of the planning horizon, all action nodes in the model are initialized to "Do nothing" state. The system is observed at every time point. If an undesirable observation is received indicating a failure condition or if proactive maintenance time comes according to the chosen strategy, the component to be maintained is determined using a separate spreadsheet environment where the efficiency measure given in Eq. (2) is calculated for each component using the posterior probabilities obtained from the DBN modeler at that time and the costs entered initially. A tabu list can also be kept and updated in the same spreadsheet and the non-tabu component with the highest efficiency measure is selected for maintenance and its action node in the DBN modeler is updated accordingly.

5. Computational analysis

Two main scenarios and for each, three sub-scenarios regarding the cost and duration of the reactive maintenance are considered. The two main scenarios are designed based on the need to stop the system during proactive maintenance times. In each scenario, various levels for the parameters (pci, pdi, thr) of proactive strategies (CIPM, DIPM, ThPM) are evaluated. Increasing the pci and pdi values or decreasing the thr values will approach the respective proactive maintenance strategies to the reactive maintenance. So, the upper (lower) limit for

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Table 2
Maintenance costs and durations.

Component	Reactive maintenance			Proactive maintenance		
	AC_i (TL)	AD_i (h)	DC_i (TL/h)	AC_i (TL)	AD_i (h)	DC_i (TL/h)
Ball Bearing (BB)	2000	1	25,000	1000	0.5	0
Winding-Insulation (WI)	15,000	4	25,000	7500	2	0
Rotor Shaft (RS)	1500	4	25,000	750	2	0
Hub Reduction Gear (HRG)	2000	2	25,000	1000	1	0
Honeycomb (Hc)	1600	6	25,000	800	3	20,000
RAH Insulation (RI)	100	2	25,000	50	1	20,000

the pci and pdi (thr) parameters are determined as the points where the respective proactive strategy reaches the reactive maintenance cost of the scenario under investigation. On the other hand, very low (high) pci and pdi (thr) values cause unnecessary proactive maintenance and result in a total cost greater than the cost of the respective proactive strategy using the nearest parameter value. According to this, the lower (upper) limit for the pci and pdi (thr) parameters are determined. Furthermore, the intermediate values are also evaluated in the analysis to represent the behavior of the maintenance strategies.

The DBN based maintenance strategies are simulated in the MATLAB environment using the BNT toolbox [36] which are run on a 300-days horizon with 30 replications for each scenario, strategy and parameter. The inference calculations are performed using the exact dynamic junction tree algorithm [38]. The tabu duration is decided such that it is not too large (then it becomes too restrictive) or too small (then it may become meaningless). So, after some experimental trials, it is set to 5 days in all computational analyses. The performance of the strategies are evaluated according to the total horizon maintenance cost. We use ANOVA models to compare the strategies. After checking the adequacy of the models, we see that all satisfy the normality. However, some models violate the constant variance assumption, hence we use Games-Howell post-hoc test to compare the strategies. Otherwise, Tukey test is used for post-hoc analysis.

5.1. Scenarios based on independent parallel motor groups

This scenario represents the real situation where the system is not required to stop for the proactive maintenance of a component belonging to the parallel motor groups, so no downtime cost incurs. However, since reactive maintenance is required when both motor groups stop, the advantage of the parallel lines is not valid in this situation. Under this main scenario, three different sub-scenarios are analyzed with different unit reactive downtime costs and durations while proactive maintenance's are kept unchanged.

5.1.1. Scenario DC_R25

This is the basis scenario where reactive and proactive maintenance costs of all components are taken as in Table 2. Scenario results are given in Table 3. Replication averages of total maintenance cost within the planning horizon are given in the "Mean" column of the table. SD and GH refer to the standard deviation and Games-Howell test result respectively. The factor levels are tabulated in decreasing values of average total cost where sharing the same GH letter indicates no significant difference among the respective average cost values. Results show that for all maintenance strategies, there is at least one parameter value that gives significantly lower cost than the reactive maintenance. Among the ones experimented, the best parameters are 5 days for CIPM and DIPM and 0.97 for ThPM. This shows that frequent proactive maintenance is needed for this scenario but it should also be avoided from unnecessary maintenance. To show the behavior of proactive maintenance strategies, the average total maintenance cost is plotted against increasing values of the parameter for each strategy and is also compared with the cost of reactive maintenance in Fig. 4.

While CIPM and DIPM behave similarly with increasing respective parameters, ThPM is like the mirror image of the two because of the reverse effect of its parameter: Increasing (decreasing) the thr (pci or pdi) parameter enables proactive maintenance activities more and hence first reduces the total horizon cost, but then increases the cost due to unnecessary proactive maintenance. DIPM and CIPM result in almost the same cost values for narrow proactive maintenance intervals, i.e, 2 and 5 days. However when the interval expands, DIPM approaches to the reactive maintenance cost quicker since it shifts the planned proactive maintenance whenever a reactive maintenance is done and hence causes less (more) proactive (reactive) maintenance compared to CIPM. So, the total cost increases due to the rising reactive maintenance number.

5.1.2. Scenario DC_R50

For the second scenario, a pessimistic approach is considered where the domestic market prices suddenly rise to a very high value such as 0.65 TL/kw whereas the agreement with the firms is made previously based on a low electricity price (0.20 TL/kw). Here, the proactive and reactive downtime costs are calculated approximately as 20,000 TL/h and 50,000 TL/h respectively. The results are shown in Table 4 and Fig. 5.

According to the results, the parameter value that gives the best results for both CIPM and DIPM is 5 days. DIPM results in higher cost than RM at intervals 60 and 90. However, as they share the same GH letter, they are not significantly different and this difference is because of the stochastic nature of the problem. In ThPM, 0.97 reliability threshold gives the minimum cost but 0.99 and 0.95 are found not to be significant than 0.97 in terms of average total cost. In Section 5.1.1, when reactive maintenance cost was 25,000 TL/h, the threshold 0.99 gave worse result than 0.97 and 0.95 which were the best. Thus, it can be concluded that as the unit downtime cost of the reactive maintenance increases, performing more proactive maintenance becomes more advantageous and hence gives lower total cost.

5.1.3. Scenario DC_R50 - 2*AD

A more pessimistic scenario is designed where there is an economic crisis and as a result of employment termination, an unplanned maintenance cannot be done expeditiously. So, the duration of the reactive maintenance actions are doubled in this scenario. Furthermore, the unit reactive cost increases to 50.000 TL/h because of the same reason described in Section 5.1.2. The results are given in Table 5 and Fig. 6.

According to the results, a proactive maintenance interval of 2 days is the best parameter for CIPM and DIPM, but this is not significantly different from 5 days. In ThPM, 0.99 gives the lowest maintenance cost, but this is not significantly different from the cost of 0.995 and 0.97. Hence, for such a pessimistic scenario where performing reactive maintenance incurs a huge cost, more frequent proactive maintenance is needed to prevent reactive maintenance. However, a reliability threshold higher than 0.99 or setting pci and pdi to one increases the total maintenance cost as a result of unnecessary proactive maintenance. It is worth to mention that ThPM is more successful in achieving a lower minimum total cost than CIPM and DIPM.

Table 3
Post-Hoc test results of scenario DC_R25.

CIPM				DIPM				ThPM			
Factor	Mean	SD	GH	Factor	Mean	SD	GH	Factor	Mean	SD	GH
RM	812,990	113,176	A	RM	812,990	113,176	A	RM	812,990	113,176	A
pci = 90	729,100	84,829	B	pdi = 90	800,813	107,055	A	thr = 0.85	794,085	136,550	A
pci = 60	658,547	116,149	B,C	pdi = 60	783,510	108,792	A	thr = 0.90	604,953	182,613	B
pci = 30	571,187	107,290	C,D	pdi = 30	714,440	138,026	A	thr = 0.99	463,040	28,197	C
pci = 2	569,843	49,779	D	pdi = 2	560,233	53,831	B	thr = 0.95	343,057	101,168	D
pci = 15	396,257	98,882	E	pdi = 15	509,553	128,893	B	thr = 0.97	303,420	58,434	D
pci = 5	339,410	56,662	E	pdi = 5	339,828	75,966	C				

Table 4
Post-Hoc test results of scenario DC_R50.

CIPM				DIPM				ThPM			
Factor	Mean	SD	GH	Factor	Mean	SD	GH	Factor	Mean	SD	GH
RM	1,508,150	181,300	A	pdi = 90	1,568,133	205,506	A	thr = 0.85	1,514,588	215,080	A
pci = 90	1,383,025	162,591	A,B	pdi = 60	1,553,275	266,095	A	RM	1,508,150	181,300	A
pci = 60	1,247,132	213,617	B	RM	1,508,150	181,300	A,B	thr = 0.90	1,093,598	286,436	B
pci = 30	1,002,885	202,155	C	pdi = 30	1,335,845	259,728	B	thr = 0.995	767,653	82,401	C
pci = 15	772,232	214,363	D	pdi = 15	899,697	245,286	C	thr = 0.95	585,782	201,297	D
pci = 2	639,673	110,493	D	pdi = 2	637,687	85,915	D	thr = 0.99	520,915	67,143	D
pci = 5	490,910	117,018	E	pdi = 5	487,282	126,608	E	thr = 0.97	447,710	167,359	D

Table 5
Post-Hoc test results of scenario DC_R50-2*AD.

CIPM				DIPM				ThPM			
Factor	Mean	SD	GH	Factor	Mean	SD	GH	Factor	Mean	SD	GH
RM	3,072,683	475,618	A	RM	3,072,683	475,618	A	RM	3,072,683	475,618	A
pci = 90	2,549,158	468,636	B	pdi = 60	3,023,847	488,502	A	thr = 0.85	3,028,380	561,275	A
pci = 60	2,468,732	360,075	B	pdi = 90	3,021,160	500,477	A	thr = 0.90	2,473,207	648,184	B
pci = 30	2,049,825	411,459	C	pdi = 30	2,643,295	660,310	A	thr = 0.999	1,539,012	129,953	C
pci = 1	1,671,372	161,985	D	pdi = 15	2,011,895	582,416	B	thr = 0.95	1,214,898	518,435	D
pci = 15	1,324,710	348,467	E	pdi = 1	1,633,573	104,908	C	thr = 0.97	833,015	264,002	E
pci = 5	877,810	202,740	F	pdi = 5	934,773	255,623	D	thr = 0.995	812,990	118,105	E
pci = 2	755,177	193,740	F	pdi = 2	774,073	169,836	D	thr = 0.99	651,698	196,147	E

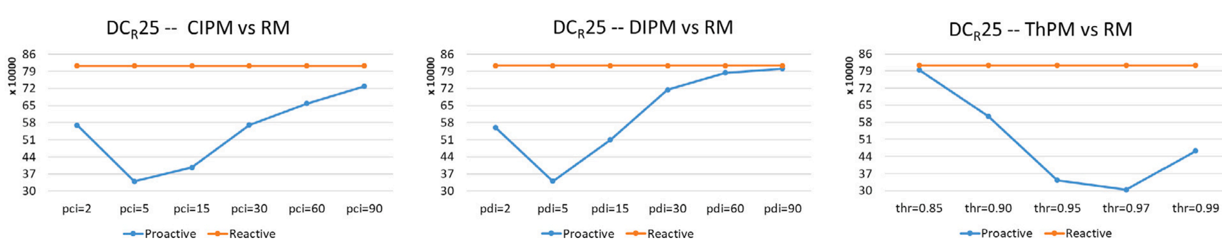


Fig. 4. Behavioral analysis of the maintenance strategies for scenario DC_R25.

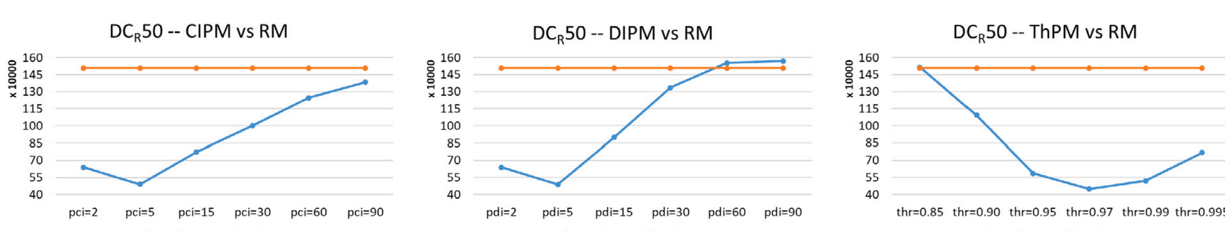


Fig. 5. Behavioral analysis of the maintenance strategies for scenario DC_R50.

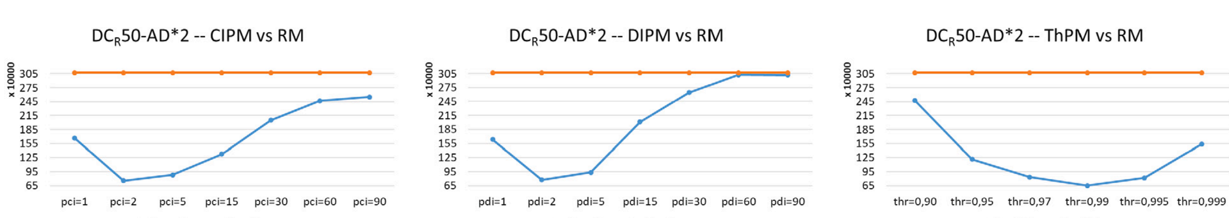


Fig. 6. Behavioral analysis of the maintenance strategies for scenario DC_R50-AD*2.

5.2. Scenarios based on dependent parallel motor groups

To see if proactive maintenance is still advantageous or not for a dependent system where system halt is needed for also the components in the parallel motor groups at proactive maintenance, another scenario is designed where the system cannot continue to work during also proactive maintenance. Hence, all activities incur a downtime cost. This scenario is simulated for all aforementioned sub-scenarios in Section 5.1.

5.2.1. Scenario depDC$_R$25

In this scenario, unit proactive and reactive downtime costs of all components are taken as 20,000 TL and 25,000 TL respectively. Maintenance durations are the same with the durations given in Table 2. Replication results for each strategy are depicted in Table 6 and Fig. 7 where Tk stands for Tukey test results. There is no parameter value that gives significantly lower cost than that of RM in all strategies. On the contrary, some parameter levels give higher maintenance cost. In CIPM and DIPM, a proactive maintenance interval of 5 days is the worst among the intervals experimented, and is also significantly different from the other parameter values and also RM. In ThPM, frequent proactive maintenance, i.e., thr = 0.97 and thr = 0.99, give the highest cost which are significantly different from each other, in addition to RM and also the other threshold levels experimented which give statistically indifferent costs with RM. Results indicate that using a proactive maintenance strategy does not gain any advantage under the cost structure given in this scenario.

5.2.2. Scenario depDC$_R$50

In this dependent scenario, the unit reactive downtime cost increases to 50,000 TL because of the reasons discussed in Section 5.1.2 whereas the unit proactive downtime cost is 20,000 TL. The results are given in Table 7 and Fig. 8. There is no parameter value that gives significantly better results than the reactive one in CIPM and DIPM. However, in ThPM, 0.97 and 0.95 thresholds are the best and give significantly lower cost than that of RM. As threshold level increases, the maintenance cost decreases, but when the threshold is 0.99, the cost increases hugely as a result of unnecessary proactive maintenance. Since ThPM achieves to give significantly lower cost than that of RM, one can conclude that, it is the best strategy in this scenario.

5.2.3. Scenario depDC$_R$50-2*AD

In addition to the previous scenario, reactive maintenance times of the components are also doubled here because of the arguments explained in Section 5.1.3. Replication results are depicted in Table 8 and Fig. 9. For each strategy, there is at least one parameter among the ones experimented that is significantly better than RM. In CIPM and DIPM, a 5 days interval gives the lowest cost significantly whereas an interval of 2 days gives the highest cost because of the unnecessary proactive maintenance. ThPM gives the lowest cost at the threshold level of 0.97 which is significantly better than RM and all threshold levels experimented other than 0.95. These results show that even if the parallel motor groups in the system are dependent, if the reactive maintenance cost is high enough, proactive maintenance provides advantage in keeping the system sustainable while reducing the total maintenance cost.

5.3. Comparison of the strategies using the best parameters

To understand which maintenance strategy is the most suitable, each strategy is compared using its best performed parameter, which gives significantly lower cost than RM, under the given scenarios using ANOVA. Scenarios depDC$_R$25 and depDC$_R$50 where none or only one (ThPM) of the strategies achieves to find significantly lower cost than RM are not considered. Table 9 shows the comparison results based on both maintenance cost and number. Results indicate that there is almost no significant difference among the strategies based on the maintenance cost, although ThPM gives the lowest cost. On the other hand, while comparing the strategies based on the maintenance number, ThPM is the best significantly. Since the real system condition is considered while deciding on the proactive maintenance in ThPM, it is only applied when necessary. Thus, ThPM achieves to decrease both maintenance number and also maintenance cost.

One may think that DIPM will lead to better results than CIPM at all proactive maintenance intervals. For very frequent proactive maintenance, DIPM results in similar cost values as with CIPM. However, as proactive maintenance interval gets wider, especially wider than the optimum interval, number of reactive maintenance increases, as proactive maintenance is shifted in DIPM, and hence gives more cost than CIPM. DIPM may give less cost for a system of a single component or of a very small number of components, But, in a multi-component system, when proactive maintenance is applied on only one component contrary to the age-based maintenance where the whole system is repaired, the results show that shifting the proactive times according to the reactive maintenance times is not advantageous compared to the preventive maintenance with fixed proactive maintenance times.

5.4. Comparison with time based strategies

To illustrate the effectiveness of the proposed DBN based maintenance decision framework, we also design a time based proactive maintenance (TBPM) strategy to be used as benchmark. TBPM is constructed such that proactive maintenance of each component in the system is scheduled according to a predetermined proactive maintenance frequency of that component in the 300 days horizon. If an emergency situation occurs after sampling the observation at the start of each period, then reactive maintenance is performed on a selected component. Scheduled proactive maintenance of that component at that time, if there exists one, is canceled. In the DC$_R$25 scenario, ThPM with thr = 0.97 gives the minimum cost and it is selected for the comparison. Not to give an unfair advantage to ThPM, similar proactive maintenance frequencies as with ThPM, i.e., {1, 4, 9, 6, 0, 3} are taken firstly for the components {BB, WI, RS, HRG, Hc, RI} respectively for TBPM and this strategy is called "TBPM.v1" of DC$_R$25. Another strategy "TBPM.v2" is generated with an alternative frequency set, {4, 3, 5, 6, 0, 4}, which is determined by almost averaging the proactive maintenance frequencies of ThPM (thr = 0.97) under DC$_R$25 and depDC$_R$25. Two methods, FEL$_{fp}$ and a random component selection method (RND) are employed as the component selection methods at reactive maintenance times for TBPM.v1. All TBPM strategies are replicated 30 times and the results are given in Table 10 where the maintenance numbers of the same components in the motor groups are aggregated.

TBPM.v1 with the FEL$_{fp}$ method gives a very close total cost as with ThPM. Because almost the same number of proactive maintenance is performed for each component and FEL$_{fp}$ is used for component selection at corrective maintenance times in both strategies. When we change the maintenance frequencies as in TBPM.v2 in the DC$_R$25 scenario, but still use FEL$_{fp}$, the cost becomes significantly different from the ThPM cost with a p-value of 0.009. It is interesting to see that proactive cost is not affected by this change in the DC$_R$25 scenario because of the zero downtime cost of the components in the parallel motor groups. Using RND component selection method with TBPM.v1 costs about twice as much as ThPM, hence results a p-value of zero. This shows the importance of the component selection method in a corrective maintenance.

In Section 5.2.1, the depDC$_R$25 scenario does not give a significantly lower cost than that of RM, and ThPM with thr = 0.97 costs significantly higher than RM. For this scenario, the maintenance frequencies in TBPM.v1 and TBPM.v2 are taken as {6, 2, 1, 5, 0, 5} and {4, 3, 5, 6, 0, 4} respectively because of the same reasons explained for DC$_R$25. TBPM strategies result significantly higher cost than that of ThPM in all cases. It is observed that some components undergo less

Table 6
Post-Hoc test results of scenario depDC$_R$25.

CIPM				DIPM				ThPM			
Factor	Mean	SD	Tk	Factor	Mean	SD	Tk	Factor	Mean	SD	Tk
pci = 5	1,371,632	84,708	A	pdi = 5	1,314,080	71,977	A	thr = 0.99	1,820,468	70,485	A
pci = 15	896,750	118,529	B	pdi = 15	860,923	128,510	B	thr = 0.97	968,652	69,521	B
pci = 90	861,858	133,908	B,C	pdi = 45	835,497	144,658	B	thr = 0.95	872,307	96,427	C
pci = 30	853,227	123,612	B,C	pdi = 60	833,427	114,897	B	thr = 0.85	822,928	139,546	C
RM	812,990	113,176	B,C	pdi = 30	817,995	107,112	B	RM	812,990	113,176	C
pci = 60	781,005	126,373	C	RM	812,990	113,176	B	thr = 0.75	806,593	104,865	C
pci = 45	776,202	133,158	C	pdi = 90	782,293	94,332	B	thr = 0.90	800,207	123,541	C

Table 7
Post-Hoc test results of scenario depDC$_R$50.

CIPM				DIPM				ThPM			
Factor	Mean	SD	Tk	Factor	Mean	SD	Tk	Factor	Mean	SD	Tk
pci = 2	3,234,358	181,300	A	pdi = 2	3,263,513	98 797	A	thr = 0.99	1,912,942	149,836	A
pci = 5	1,610,330	217,801	B,C	pdi = 30	1,607,462	241,444	B	thr = 0.85	1,606,567	229,963	B
pci = 90	1,608,683	229,191	B,C	pdi = 60	1,595,673	233,141	B	RM	1,508,150	181,300	B,C
pci = 60	1,559,500	207,912	B,C	pdi = 90	1,574,220	249,517	B,C	thr = 0.90	1,397,760	244,947	C,D
pci = 45	1,555,900	175,201	B,C	pdi = 5	1,560,697	168,177	B,C	thr = 0.95	1,260,420	220,126	D,E
RM	1,508,150	181,300	B,C	pdi = 45	1,525,210	269,834	B,C	thr = 0.97	1,228,858	217,561	E
pci = 30	1,447,768	221,860	B,C	RM	1,508,150	181,300	B,C				
pci = 15	1,400,557	186,110	C	pdi = 15	1,395,637	236,102	C				

Table 8
Post-Hoc test results of scenario depDC$_R$50-2*AD.

CIPM				DIPM				ThPM			
Factor	Mean	SD	GH	Factor	Mean	SD	GH	Factor	Mean	SD	GH
pci = 2	3,411,912	271,384	A,B	pdi = 2	3,459,180	261,008	A	RM	3,072,683	475,618	A
RM	3,072,683	475,618	B	RM	3,072,683	475,618	B	thr = 0.85	2,991,852	546,488	A
pci = 90	3,062,532	390,982	B	pdi = 90	3,046,507	459,494	B	thr = 0.90	2,675,882	620,795	A
pci = 60	2,914,787	390,891	B,C	pdi = 60	2,972,570	407,950	B	thr = 0.99	2,089,465	268,921	B
pci = 30	2,896,617	457,727	B,C	pdi = 30	2,877,380	523,580	B,C	thr = 0.95	1,833,235	497,400	B,C
pci = 15	2,554,793	514,663	C	pdi = 15	2,550,208	456,090	C	thr = 0.97	1,777,223	415,788	C
pci = 5	1,867,830	411,877	D	pdi = 5	1,900,833	328,620	D				

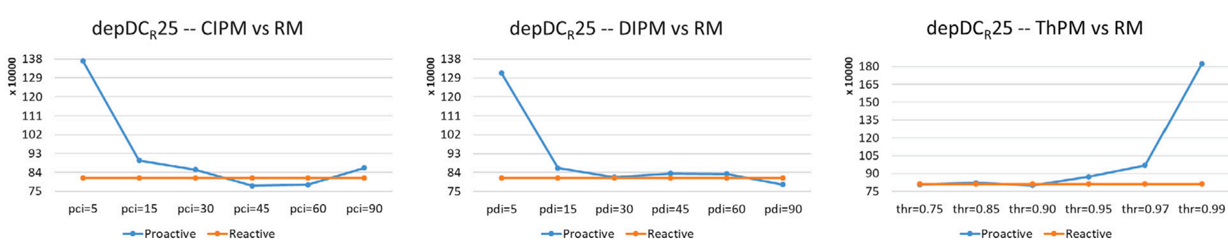


Fig. 7. Behavioral analysis of the maintenance strategies for scenario depDC$_R$25.

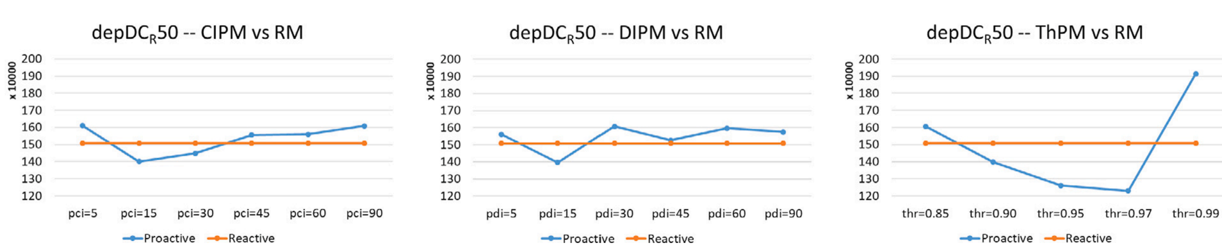


Fig. 8. Behavioral analysis of the maintenance strategies for scenario depDC$_R$50.

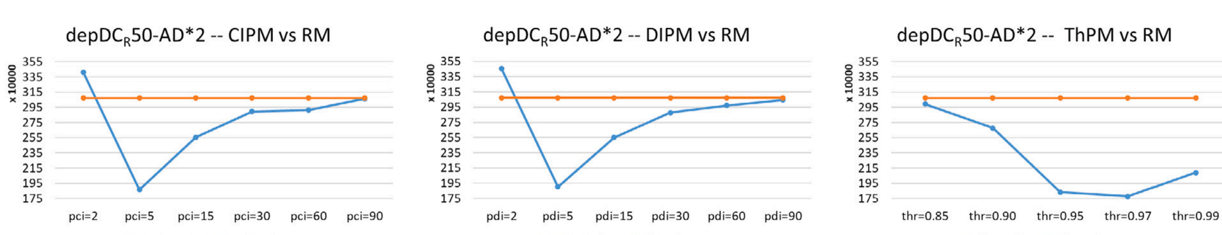


Fig. 9. Behavioral analysis of the maintenance strategies for scenario depDC$_R$50-2*AD.

Table 9
Comparison of the best parameters of the strategies under different scenarios.

Scenario	Parameter	Cost	SD	Tk	Parameter	Number	SD	GH
DC_R25	pdi = 5	339,828	75,966	A	pci = 5	65.00	1.702	A
	pci = 5	339,410	56,662	A	pdi = 5	62.20	1.243	B
	thr = 0.97	303,420	58,434	A	thr = 0.97	51.30	4.348	C
DC_R50	pci = 5	490,910	117,018	A	pci = 5	65.57	1.716	A
	pdi = 5	487,282	126,608	A	pdi = 5	62.77	1.524	B
	thr = 0.97	447,710	167,359	A	thr = 0.97	49.20	3.624	C
DC_R50-2*AD	pdi = 2	774,073	169,836	A	pci = 2	150.67	1.155	A
	pci = 2	755,177	193,740	A,B	pdi = 2	150.27	0.785	A
	thr = 0.99	651,698	196,147	B	thr = 0.99	100.50	3.481	B
depDC_R50-2*AD	pdi = 5	1,900,833	328,620	A	pci = 5	63.00	2.197	A
	pci = 5	1,867,830	411,877	A	pdi = 5	61.40	1.276	B
	thr = 0.97	1,777,223	415,788	A	thr = 0.97	40.93	2.116	C

Table 10
Comparison with time based strategies under DC_R25 and depDC_R25.

		Scenario DC_R25								Scenario depDC_R25							
Strategy Method		BB	WI	RS	HRG	Hc	RI	Cost	TotCost P-value	BB	WI	RS	HRG	Hc	RI	Cost	TotCost P-value
ThPM(0.97)	PM	3.50	8.40	18.20	13.80	0.00	3.27	159,447	303,420	12.97	3.77	2.00	11.00	0.00	5.90	752,345	968,652
FEL_{fp}	RM	2.87	0.03	0.00	0.50	0.00	0.73	143,973	–	3.10	0.20	0.10	1.37	0.00	0.57	216,307	–
TBPM.v1	PM	2.00	8.00	18.00	12.00	0.00	3.00	147,650	329,677	11.63	4.00	2.00	9.97	0.00	4.97	708,348	1,233,308
FEL_{fp}	RM	3.07	0.20	0.00	0.57	0.00	0.93	182,027	0.107	4.27	1.33	1.10	2.37	0.00	0.43	524,960	0.000
TBPM.v2	PM	8.00	6.00	10.00	12.00	0.00	4.00	152,700	348,797	8.00	6.00	10.00	12.00	0.00	4.00	1,112,700	1,343,757
FEL_{fp}	RM	2.33	0.03	0.00	1.23	0.00	1.30	196,097	0.009	2.90	0.13	0.00	1.13	0.00	1.57	231,057	0.000
TBPM.v1	PM	2.00	8.00	18.00	12.00	0.00	3.00	147,650	654,113	11.97	4.00	2.00	10.00	0.00	5.00	713,383	1,466,777
RND	RM	1.13	1.40	1.27	0.93	0.63	0.83	506,463	0.000	1.90	1.93	1.97	1.73	1.00	0.77	753,393	0.000

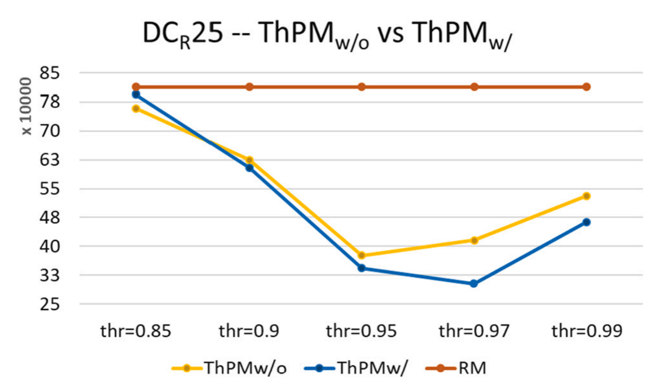


Fig. 10. Comparison of with and without tabu procedure with ThPM under DC_R25.

proactive maintenance than the schedule in this scenario since they are selected for corrective maintenance at the start of their proactive maintenance time. Although proactive costs of TBPM.v1 are very close to that of ThPM, TBPM.v2 results in significantly higher proactive cost. This is because of the fact that in TBPM.v1, almost the same number of proactive maintenance as with ThPM is performed for each component. But, the frequency differs in TBPM.v2 and each component has a nonzero downtime cost in depDC_R25. The results emphasize the importance of making accurate time and activity decisions in achieving a cost effective proactive maintenance policy. A TBPM strategy can be improved by trying different component maintenance frequencies, but this will not be enough when components have significantly different maintenance costs. The results show the effectiveness of the FEL_{fp} method in component selections at both reactive and proactive maintenance times.

5.5. Justification of using the tabu procedure

In order to justify the usage of tabu procedure within the maintenance decision making process, we also replicate ThPM without using the tabu procedure. The total maintenance cost of ThPM under the DC_R25 scenario is plotted against increasing thr values in Fig. 10 for the respective two cases. The biggest difference according to the cost value belongs to thr = 0.97 which gives also the lowest cost with the tabu procedure. After conforming the normality assumption, t-test is performed to statistically compare the cost performance with (w/) and without (w/o) tabu at all parameter levels. A *p*-value of zero is obtained for thresholds 0.97 and 0.99 whereas no significant difference is encountered at the others. The results are reasonable when we consider that as the threshold decreases, the proactive maintenance frequency also decreases which results in an empty tabu list in almost all proactive maintenance periods. On the other hand, when threshold is 0.99, although we have a *p*-value of zero, the cost difference gets smaller compared to the previous thresholds since tabu procedure with a duration of 5 becomes too restrictive because of a long tabu list at a proactive maintenance time.

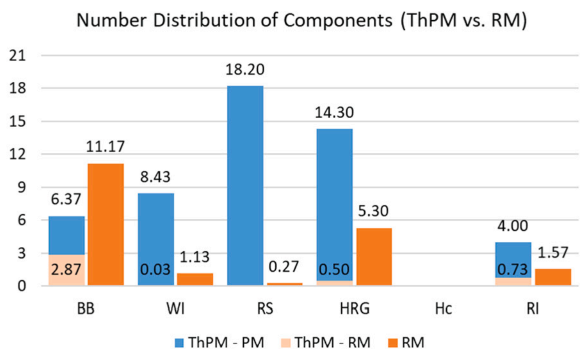
We also analyze the distribution of the components that undergo proactive and reactive maintenance under the ThPM strategy (thr = 0.97) with and without tabu procedures in Table 11. The results are really remarkable since a huge number of proactive maintenance is performed on the RS components in the w/o tabu case. At a threshold level of 0.97, proactive maintenance is performed frequently and components have high and similar reliabilities which makes the cost values more effective during component selection at proactive maintenance periods. Since RS has the lowest proactive maintenance cost, it is selected repeatedly indicating that the solution procedure gets stuck at proactive maintenance times. When w/ tabu results are analyzed, the distribution is more balanced because prohibitions (henceforth the term tabu) are introduced to discourage the maintenance activity search from repeating the recently selected components.

5.6. Number and cost distribution of the components

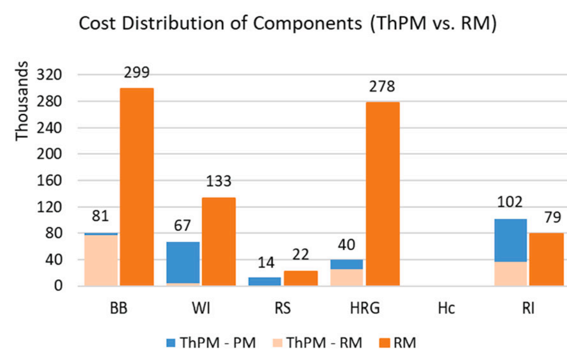
Fig. 11 depicts the distribution of the RAH components with ThPM (thr = 0.97) and RM strategies in terms of number and cost under DC_R25. Blue and light orange bins represent the proactive and reactive maintenance within ThPM whereas orange bins show the maintenance

Table 11
Distribution of components with and without tabu procedure at thr=0.97.

		BB1	WI1	RS1	HRG1	BB2	WI2	RS2	HRG2	Hc	RI	Total	SD
w/o Tabu	PM	0.00	3.23	50.47	6.23	0.00	2.97	48.87	6.60	0.00	1.13	127.17	24.83
	RM	2.90	0.00	0.00	0.30	2.53	0.00	0.00	0.10	0.00	1.83		
w/ Tabu	PM	1.73	4.37	8.77	6.77	1.77	4.03	9.43	7.03	0.00	3.27	51.30	4.35
	RM	1.47	0.03	0.00	0.13	1.40	0.00	0.00	0.37	0.00	0.73		



(a) Number distribution



(b) Cost distribution

Fig. 11. Distribution of components with respect to number and cost under DC_R25.

within RM. Fig. 11a shows that WI and RS are very seldomly selected to be maintained at reactive maintenance times of both ThPM and RM strategies. Instead, BB comes into prominence for selection because of its least action duration and consequently low maintenance cost. In ThPM, the most frequent proactive maintenance belongs to RS and HRG due to their action costs, posterior probabilities and zero downtime costs. This is also verified by Fig. 11b where these components give the lowest proactive maintenance cost despite of their highest quantities. Although WI is also a part of the motor group, it is not preferred as many as RS and HRG at proactive maintenance times in ThPM. However, WI has more share in the cost distribution of components compared to RS and HRG due to its high action cost.

5.7. Sensitivity to the maintenance cost of the honeycomb

Honeycomb is never maintained at both proactive and reactive maintenance by ThPM (thr = 0.97) under the DC_R25 scenario as seen in Fig. 11a. This is mostly because of its highest maintenance cost due to its action duration which are 3 and 6 h at PM and RM respectively. In order to see at which duration level Hc will start to be selected for maintenance, its action duration is decreased gradually in both DC_R25 and depDC_R25 scenarios. Hc is included within the maintenance activities when its action duration at PM (RM) is 0.5 (1) in the DC_R25 scenario whereas it starts to be maintained earlier in the depDC_R25 when its duration at PM (RM) is 1 (2) as seen in the replication results given in Table 12. The reason why it is not maintained in the Hc(1-2) case in the independent scenario is that here, Hc and RI have the highest cost in PM, followed immediately by WI. Hence, RS, HRG and BB are highly preferred for maintenance by the FEL_{fp} method in PM times since they have zero downtime cost and very low action cost. Although WI is also in the parallel motor group, as the action duration of Hc decreases, WI is maintained less which is contrary to the general behavior of RS, HRG and BB due to its high action cost. Nevertheless, RS does not have any cost advantage over WI in the dependent scenario because of its high downtime cost in PM due to its high action duration. Therefore it is not preferred much for maintenance compared to BB and HRG in depDC_R25. Another important finding is that, here, Hc is maintained proactively rather then reactively with the decreasing action duration since it has downtime cost advantage which is not valid in DC_R25.

6. Conclusion

We propose a maintenance decision framework where DBNs are used to model the dependencies, deterioration and partial observability in a complex system, and to provide an efficient environment for evaluating proactive maintenance strategies. A generic DBN based proactive maintenance algorithm with a tabu procedure is developed within the proposed decision framework with the aim of reducing the horizon maintenance cost. Two preventive and one predictive maintenance strategies from a cost perspective are evaluated. Their performances are compared with each other and also with the reactive maintenance strategy on a real system available in thermal power plants under six different scenarios using different policy parameters. Although all proposed proactive strategies provide satisfactory results, as threshold based maintenance is a predictive policy deciding the maintenance time by considering the system reliability, it gives the minimum cost for almost all scenarios. Moreover, the threshold based strategy is also successful in decreasing maintenance number in addition to the cost which may position it as a more preferable policy in industries where the production should continue with minimum downtime. Comparison with time based proactive strategies show the effectiveness of the component selection method at both reactive and proactive maintenance times.

The considered system is a large and complex structure whose malfunction or halt causes a serious downtime cost. Even when it is entered inside for maintenance, it is very time-consuming and difficult to find out where the failure has originated. Especially in time-sensitive structures like this, precise inspection is quite costly. Therefore, it makes more sense to approach the system as partially observable at both reactive and proactive maintenance times. Boiler and furnace systems can be counted as similar systems, having interacting components with limited observability, where the proposed maintenance decision framework can be implemented.

In this study, the maintenance activities are labor and equipment oriented and their durations are provided tightly given the allocated resource. Group maintenance is possible but with longer maintenance durations. Hence, it is assumed that only one component can be repaired at a time point. As a future study, one can include opportunistic maintenance perspective within the decision framework.

Table 12
Distribution of components with different Hc action durations.

Hc		Scenario DC_R25						Scenario $depDC_R25$					
(Duration)		BB	WI	RS	HRG	Hc	RI	BB	WI	RS	HRG	Hc	RI
Hc(3–6)	PM	3.50	8.40	18.20	13.80	0.00	3.27	12.97	3.77	2.00	11.00	0.00	5.90
	RM	2.87	0.03	0.00	0.50	0.00	0.73	3.10	0.20	0.10	1.37	0.00	0.57
Hc(1–2)	PM	7.43	6.03	23.77	21.23	0.00	2.40	23.43	2.90	2.10	15.00	0.87	7.80
	RM	3.23	0.00	0.00	0.20	0.00	1.07	4.90	0.23	0.00	1.00	0.03	0.50
Hc(0.5–1)	PM	14.93	5.40	29.57	26.53	0.00	1.10	22.77	3.00	1.93	11.13	5.07	2.87
	RM	2.87	0.00	0.00	0.13	1.37	1.07	3.80	0.20	0.13	1.00	1.40	0.13

CRediT authorship contribution statement

Demet Özgür-Ünlüakın: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Project administration, Funding acquisition. **Busenur Türkali:** Software, Validation, Formal analysis, Investigation, Writing - original draft, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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